

## MISR-CERES Narrow-to-Broadband Results

using coincident views from MISR and CERES (along track SSF) on Terra

integrates MISR spectral radiances over CERES footprint using PSF and compares with CERES broadband SW

Greg Markowski Roger Davies



Jet Propulsion Laboratory
California Institute of Technology
Pasadena, CA 91109

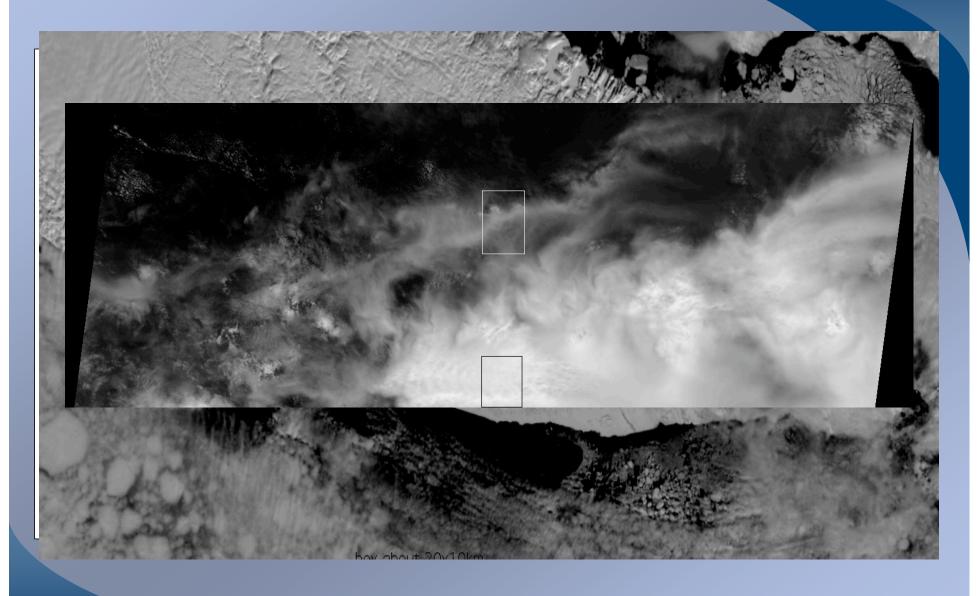
#### Narrow-broadband Issues

- generic single band regression
  - overall rms (camera specific)
- prospects for multi-band regression
  - lessons learned from residual outliers
    - cloud height
    - scene heterogeneity
  - likely scene candidates
  - "Information orthogonal" approach
- prospects for accurate prediction of rms error
  - magnitudes
  - good versus bad scene types
- future work

#### Generic MISR Single-band Results

- Overall rms, typically:
  - Camera AN r = 0.985 0.993, rms = ~15%, or ~10 W/m<sup>2</sup>/sr
  - Cameras DF, AA r = 0.96 0.99, rms = ~20%, or ~18 W/m<sup>2</sup>/sr
- Considerable rms differences between bands
  - rms increases with camera angle
  - blue band has highest rms error
  - outlying errors can vary considerably along orbit (non-Gaussian)
- generic rms error is large ~10 W/m²/sr (seeking ≈ 3)
- ⇒ next consider multiple regression and scene type
  - Using "information orthogonalization" to treat very high cross-correlation between
     MISR spectral bands (blue, green, red, near ir: 446, 558, 672, 866 nm)

# Mulltiband Regression Residual Analysis (an example)



#### SCENE GROUPINGS CURRENTLY IN USE

```
1) all data in each band
                          3) for UNDEFINED scenes only
5) for snow cover only
                          7) for clear ocean only
9) for clear land only
11) for ocean, partly cloudy
                                     thin liquid clouds
13) for ocean, moderately cloudy
                                    thin liquid clouds
15) for ocean, mostly cloudy
                                     thin liquid clouds
17) for ocean, overcast
                                     thin liquid clouds
19) for ocean, partly cloudy
                                     thick liquid clouds
21) for ocean, moderately cloudy
                                     thick liquid clouds
23) for ocean, mostly cloudy
                                    thick liquid clouds
25) for ocean, overcast
                                    thick liquid clouds
27) for ocean, partly cloudy
                                     thin ice clouds
29) for ocean, moderately cloudy
                                     thin ice clouds
31) for ocean, mostly cloudy
                                     thin ice clouds
33) for ocean, overcast
                                     thin ice clouds
35) for ocean, partly cloudy
                                    thick ice clouds
37) for ocean, moderately cloudy
                                    thick ice clouds
39) for ocean, mostly cloudy
                                     thick ice clouds
41) for ocean, overcast
                                     thick ice clouds
43) for land, partly cloudy
                                     thin liquid clouds
45) for land, moderately cloudy
                                    thin liquid clouds
47) for land, overcast
                                     thin liquid clouds
49) for land, partly cloudy
                                     thick liquid clouds
51) for land, moderately cloudy
                                     thick liquid clouds
53) for land, overcast
                                    thick liquid clouds
55) for land, partly cloudy
                                     thin ice clouds
57) for land, moderately cloudy
                                     thin ice clouds
59) for land, overcast
                                     thin ice clouds
61) for land, partly cloudy
                                     thick ice clouds
63) for land, moderately cloudy
                                     thick ice clouds
65) for land, overcast
                                    thick ice clouds
```

#### Variable orthogonalization:

Subtract out successive residuals from residual series that have not yet been orthogonalized until no info left

Pick a MISR band to become the first variable Calculate the residuals for each series not yet a variable Pick the next residual series to become a variable Repeat (N - 1 times)

# Orthogonal Multiple Regression for scene groups & Improvement without outliers

SCENE TYPE	# PTS C	CAMER	A	COEFF	CIENTS		$\sigma_{y.x}$	RELSIG	R <sub>mult</sub>
all scenes	2793	AN		0.406	0.197	-0.146	3.4	0.069	0.998
all scenes	2696	AN		0.407	0.203	-0.083	2.6	0.055	0.998
<del>-</del>									
snow	1151	AN		0.417	0.287	-0.141	2.5	0.059	0.998
snow	1110	AN		0.428	0.249	0.231	1.8	0.044	0.999
Clear_ocean	360	AN			0.196	0.071	0.8	0.114	0.993
Clear_ocean	352	AN		0.346	0.193	0.080	0.7	0.102	0.995
							_		
ocn_liq_pc_thin	158	AN		0.207	0.220	0.119	1.5	0.121	0.993
ocn_liq_pc_thin	154	AN		0.218	0.247	0.091	1.3	0.111	0.994
ocn_liq_mstc_thn	125	AN			0.314	-1.413	3.6	0.105	0.995
ocn_liq_mstc_thn	120	AN		-0.465	0.327	-1.333	2.8	0.083	0.997
	120	7.37		0 010	0 210	0.770	2 6	0 000	0.006
ocn_liq_ovrc_thn	130	AN		-0.018	0.310	-0.770	3.6	0.090	0.996
ocn_liq_ovrc_thn	126	AN		0.126	0.262	-0.732	2.9	0.072	0.997
ocn ice ovrc thn	151	AN		-0.216	0.220	-1.406	2.3	0.072	0.997
ocn_ice_ovrc_thn	144	AN			0.361	-0.672	1.5	0.072	0.999
ocn_ice_ovic_ciiii	111	AIN		-0.170	0.301	-0.072	1.3	0.031	0.000
ocn ice ovrc thk	122	AN		0.167	-0.274	-0.070	2.2	0.032	0.999
ocn ice ovrc thk	118	AN	0.531		-0.314	0.552	1.9	0.027	1.000
ocn liq modc thn	180	DA		-0.012	0.833	-1.373	6.4	0.445	0.896
ocn liq mode thn	178	DA		0.126	0.702	-0.351	6.1	0.431	0.902
ocn_liq_mstc_thn	58	DA		0.420	0.736	-2.496	6.9	0.365	0.931
ocn_liq_mstc_thn	57	DA		0.243	1.281	-1.483	6.0	0.316	0.949

← 2nd
rows
←show
outliers
removed

(1 orbit)

#### Other Issues and Future Work

- Apply MISR stereo heights
  - to account for water vapor absorption
- Filter out heterogeneous scenes
  - by brightness variation and cloud height variation
- Apply to a much larger dataset
  - Have put considerable effort into speeding up our basic MISR to CERES comparison code

#### Also

- Need to know instrument time constant
  - to compare MISR and CERES data footprint weighting
- Consider adding other factors: solar zenith angle, relative azimuth angle, scattering angle, ozone proxy
- Consider color indices, especially for clear land scenes

#### **Progress Summary**

- we have obtained considerable prediction improvement
   vs. generic scene single band
- scene heterogeneity seems (currently) to cause the greatest prediction errors
- high bright clouds should be treated as separate class
- best guess error for stratified scenes, multiple regression,
   ≈2 W m<sup>-2</sup> sr<sup>-1</sup>



# MISR-CERES Narrow-to-Broadband Results

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#### Effect of removing largest outliers

- Scene classifications used (show table) and results (show chart, include all scenes results & and without and with all outliers removed, use numerical output if out of time this week)
- results may be limited by remaining heterogeneous scenes

# Multiple-regression for specific scene types Effect of removing largest outliers

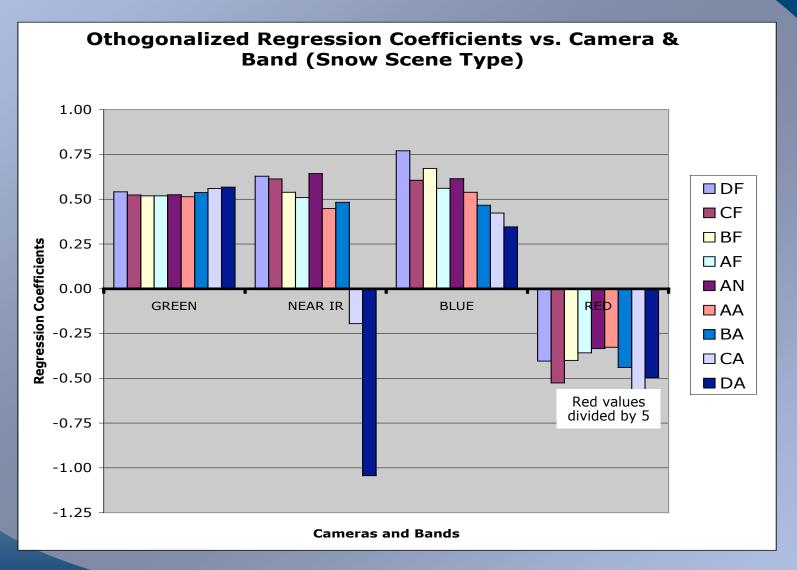
- Main difficulty: MISR measurements are highly correlated. (Table showing typical band cross-correlation)
- a. High x-correlations suggest that little information can be added by using more than 1 or 2 bands.
- b. ? The above not necessarily true. (Show RMS error.)
- c. Information Orthogonalization: Shows where the information is. (Show diagram + statistics example)
  - » i. ? Show example: r for each successive band added
  - » ii. Show example: change in coefficients versus several cameras, with & without orthogonalization (bar chart)
  - » iii. Discuss disadvantages + solution, hopefully
- or simply show the before and after: may not have enough time for lots of depth here.

# Multiple-regression for specific scene types Effect of removing largest outliers

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ocn liq mstc thn	120				0.314	-1.413	2.8	0.103	0.993
ocii_iiq_iiiscc_ciiii	120	TIN.		-0.403	0.327	-1.555	2.0	0.003	0.991
ocn lig ovrc thn	130	AN		-0.018	0.310	-0.770	3.6	0.090	0.996
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	100					4 050			0.006
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ocn lig mstc thn	50 57			0.420	1.281	-2.496 -1.483	6.0	0.365	0.931
ocii_ttd_macc_ciii	37	DA		0.243	1.201	-1.403	0.0	0.510	0.943

✓ 2nd rows show outliers removed

#### **Stabilization of Regression Coefficients**



### Mulltiband Regression Residual Analysis (an example)

